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ANN BASED OPTIMIZATION MODEL FOR DIE CASTING OF ALUMINIUM ALLOY LM6

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ABSTRACT

In the current research work the optimization of process parameters of an aluminium alloy diecasting operation is discussed. The major defect causing quality issue during the manufacturing of a die casted component was identified as porosity. An analysis of variance (ANOVA) is carried out to trace the parameters with significant effects on porosity. The plunger pressure used in the die casting machine the liquid aluminium temperature are identified as significant factors after ANOVA. Afterwards a BP-ANN is modelled and trained with the two significant factors and porosity in order to predict output by optimizing the two input process parameters. Further, the calculated values from a regression analysis are graphically compared with predicted ANN model in order to validate the ANN model.

KEYWORDS: Optimisation, ANOVA, Porosity & Regression Analysis

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Original Article

INTRODUCTION

Porosity in the die casting industry leads to tremendous loss in the profit margins as the quality of the product is highly affected. This also leads to the generation of scrap which is always undesired. Hence the quality issues generated due to porosity defect need to be addressed. The conventional trial and error based die design and process development is both costly and time taking. In order to cut down the cost and time, an efficient optimisation model based on BP-ANN (Back propagation ANN) is developed. In order to achieve this optimization tools such as tools like fuzzy logic, NN and genetic algorithm as reported in several works [1-2-3] are widely used. The beauty of these soft computing tools is that more complex and complicated the process parameters relationships are, the better the suitability of implementing soft computing tools. However before the application of each soft computing tool it is necessary to identify the process parameters which would affect the output the most. In order to achieve this cumbersome task, ANOVA and Taguchi method are used. With help of ANOVA and Taguchi method, one can easily identify the key process parameters. Also ANOVA and Taguchi method help us in determining the optimum level of the key input parameters. Some of the important research work done in the field of application of Taguchi method and DOE to die casting can be found in references [4-5-6-7-8] & [9].The current research work follows a composite approach of identifying the significant factors affecting porosity in die casted components(a quality problem) and then modelling of back propagation ANN to optimize the process.

PROBLEM IDENTIFICATION AND ANOVA

The experimental data is gathered from an ISO 9001-2008 certified SME established in 1978 located in Sirdo Industrial estate, Ranchi. It is a manufacturer of pressure and gravity die castings. The range of the products

includes castings for tele-communications, defence, business machines, electrical equipments and general engineering. The components are die casted using cold chamber die casting machines before machining them to the required specifications. The aluminium alloy lm6 used for manufacturing the defence component in the current research work is LM6.The typical composition of the aluminium alloy is given below:

Copper: 3 to 3.5%, Silicon: 0.7%, Magnesium: 0.10%, Iron: 0.6%, Manganese: 0.5%, Nickel: 0.1%, Zinc: 0.1%, Lead: 0.1%, Aluminium: Rest

The cold chamber die casting machine is fully equipped with appropriate instrumentation for the required data acquisition, and monitoring system for the analysis and investigation of the various die casting parameters.

During quality assessment of the components produced by cold chamber die casting, it was observed that the major issue encountered was the porosity. The porosity problem is directly linked to the density of the component, which is chosen as it would be convenient to measure the same. To begin with a cause and effect analysis is conducted in order to identify the various process parameters influencing the output i.e., porosity in the die castings. The four key factors identified through that cause and effect analysis are listed below:-

- Molten metal temperature
- Plunger velocity
- Hydraulic pressure and
- Metal filling time

The range of the molten metal temperature was selected at 610 -730^{0}C, while the plunger velocity in the first stage was selected at 0.03-0.70 m/s and in the second stage it was selected at 1.3-3.9 m/s. Further, the range of hydraulic pressure was chosen to be 120-123 Bars and the filling time range was selected between 45 to135 ms (millisecond). While selecting the range of these process parameters, the constraints imposed by the die casting set up was kept in mind. The five process parameters are designated as A, B, C, D& E for convenience and each parameter is taken at two levels. The multilevel of the parameters is necessary to be taken in order to determine the nonlinear behaviour of the parameters of the die casting process. The process parameters with their upper and lower levels are listed in the table 1 below.

Table 1: Process Parameters with their Values at Two Levels

Parameter Designation	Process Parameters	Level 1	Level 2
A	Molten metal temperature (ºC)	610	730
B	Plunger velocity first stage (m/s)	0.03	0.70
C	Plunger velocity second stage (m/s)	1.3	3.9
D	Hydraulic pressure (Bars)	120	123
E	Metal filling time (ms)	45	135

Further an orthogonal array (OA) is used to identify the significant parameters which would have considerable effect in the casting density. An orthogonal array is basically a fractional factorial matrix which assures a balanced

comparison of levels of any factor or interaction of factors [10]. An orthogonal array is represented in form of a matrix where the rows represents the level of factors in each run and each column represents a particular factor that can be changed from each run. An L_8 (2^7) is chosen for solving the current quality problem where five factors have two levels each. During the significance testing the interaction between the factors is not considered and hence the last wo columns of the chosen orthogonal array remain unassigned. Factor A i.e., molten metal temperature is assigned to column 1, factor B assigned to column 2 and so on in that order till factor E is assigned to column 5 of the array. Afterwards, the eight experimental trials are carried out as per the level settings for the various factors in the orthogonal array and the observations are listed in the Table 2 below. During the die casting, eight component samples are produced in each trial and their respective densities are listed in the table 2 below.

Table 2: Densities (gm/cm^3)of Eight die Casting Samples under each Trial of L_8 OA

Trial	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1	2	2	2.224	2.064	2.32	2.14	2.065	2
2	2.063	2.317	2	2.142	2.318	2.418	2.482	2.226
3	2.064	2	2	2.254	2.064	2.142	2.317	2.226
4	2.062	2.066	2	2.224	2.14	2.48	2.418	2.004
5	2.062	2	2.227	2.065	2	2.421	2.418	2.47
6	2.47	2.49	2.317	2.065	2.32	2	2.14	2.418
7	2.316	2.065	2	2.142	2.48	2.494	2.48	2.42
8	2.418	2.42	2.48	2.47	2.419	2.49	2	2.48

The next step is to go for the analysis of variance i.e., to construct the ANOVA table. In order to do so, the calculation for sum of squares (SS) of factors and errors is done and is listed in Table 3. The variances are further calculated by dividing the sum of squares by their corresponding degree of freedom. The degree of freedom (v) is calculated by subtracting one from the number of levels of each factor. The $F_{data}$for all the factors are obtained by using the variance of error. The value of F_{table} is obtained from the statistical table and the significance is tested by comparing the values of F_{data} and F_{table}. After the comparison of the two values, it is observed that the F_{data} is greater than F_{table} for two sources A and D. Hence it becomes clear from ANOVA table that the two significant factors affecting the casting density are the molten metal temperature (A) and the hydraulic pressure (D).

Table 3: ANOVA Table for Die Casting Density Taken at 90% Confidence Level

Source	*SS*	*v*	*V*	F_{data}	F_{table}	Significance
A	2.222	1	2.222	31.29	8.53	$F_{data}>F_{table}$
B	0.235	1	0.235	3.30	8.53	
C	0.504	1	0.504	7.09	8.53	
D	0.991	1	0.991	13.95	8.53	$F_{data}>F_{table}$
E	0.002	1	0.002	0.002	8.53	
e	0.142	2	0.071	F_{table} at 90% confidence level		
Total	**4.096**	**7**	**0.585**			

With the completion of the ANOVA table, the significant parameters affecting the casing density are identified and an artificial neural network model is developed using the two significant parameters and the casting density show that the controllable factors can be predicted to get the desired output.

ANN MODEL DIE CASTING OPTIMISATION

ANN refers to the computing systems whose fundamental concept is taken from analogy of biological neural networks. Many day to day tasks involving intelligence or pattern recognition are extremely difficult to automate, but appear to be performed very easily by animals. The neural network of an animal is part of its nervous system, containing a network of specialized cells called neurons (nerve cells). ANN s are far too simple to serve as realistic brain models on the cell levels, but they might serve as very good models for the essential information processing tasks that organism perform.

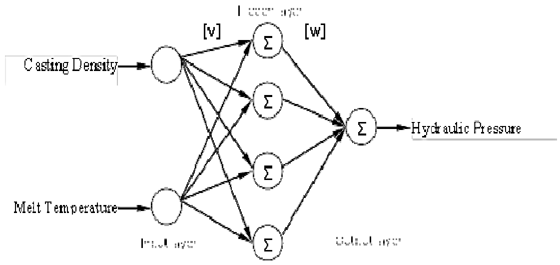

Figure 1: ANN Architecture Showing Input and Output Parameters.

The two inputs of the newly developed multi-layer feed forward ANN model as shown in figure 1 above are casting density and molten metal temperature while the output is the casting density. The aim of generating the ANN model is to find the values of the two controllable factors for a desired casting density. In order to achieve this, the casting density is taken as input parameter to predict the hydraulic pressure for given values of input parameters. As the objective of the model is to find the values of two controllable factors for a required casting density, hence the casting density is used as input to find the unknown hydraulic pressure for a given set of input parameters.

The terms [v] & [w] in figure 1 basically represent the weights between the input-hidden layers and hidden-output layers respectively. The ANN model can predict the output for a given set of inputs only after proper training. In order to train the ANN model for optimisation purpose, a set of input and out data are required from the die casting experimentally. The weights v and w are selected in such a way that the errors ate minimised for further output predictions.

DIE CASTING DATA COLLECTION AND ANN MODEL TRAINING

During the cold chamber die casting of Aluminium alloy LM6, the experimental data is collected for three parameters i.e., molten metal temperature, hydraulic pressure and last but not the least, casting density. The experimental data collected are then normalised in a range of 0 to 1 in order to minimise the variation. The other reason for normalisation is to prevent the saturation of the sigmoid function. The collected data (x) are normalized using relation (1)

$$Normalized\ value = \frac{(x - min.value)}{max.value - min.value} \tag{1}$$

The ANN modelling consists of two stages. In stage I i.e., the feed forward stage, the input data is fed to the model and the output is calculated. Further in stage II, the output is compared to the desired output from the training data set and the error is calculated. This error is used to modify the weights v and w in order to get more and more accurate result. Hence this model is rightly called as back propagation ANN. The modelling, simulation part of ANN is done in the Matlab tool box. THE Matlab toolbox has all the necessary predefined functions for pre-processing and post-processing of data. This is needed to improve the rate of convergence and accuracy.

IMPLEMENTATION OF ANN MODEL

Before using the newly developed ANN model for optimisation purpose, the model needs to be tested and validated. For this very purpose the experimental data which is collected is divided into three sets. To test and validate the model, the experimental data is divided into three sets. The first set consists of 70% of the experimental data which are used for training purpose and weight adjustments in order to minimise the error. The rest 30% of experimental data is divided into two equal groups (15% each), one of which is for validating the generalisation while the other set is used as a completely independent set which provide an independent measurement of the model performance.

The mean squared error (MSE) during training, validation and testing are found to be 1.92420e-1, 3.27484e-2 & 1.35652e-1 respectively. The MSE is basically an estimator which gives which gives a measurement of the averages of the squares of the deviations or errors or in other words, the difference between the estimator and what is estimated. Hence the lower values of MSE mean more accurate results.

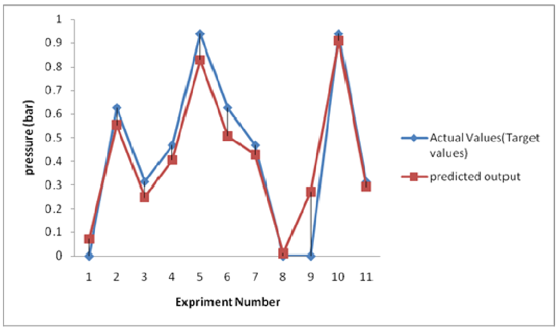

Figure 2: Comparison of Predicted and Actual Output Pressure

VALIDATION USING REGRESSION ANALYSIS

The regression analysis is a useful statistical tool which is widely used to determine the probable change in one variable for some given amount of change in another variable. This means that the value of an unknown variable can be determined from the known value of another variable. In order to apply the regression analysis in the current research problem, the experimental data is collected for the three parameters i.e., casting density, melt temperature and hydraulic pressure. The regression equation is generated in MINITAB using the experimentally collected data and is give below as equation 2.

$$z = 0.369 + 0.047\, x + 0.002\, y \qquad (2)$$

Where, z = hydraulic pressure, x = melt temperature and y = casting density

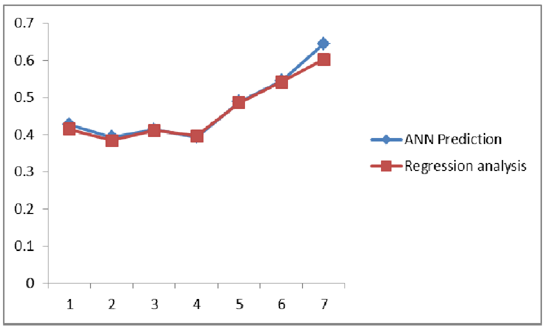

Figure 3: Comparison between ANN and Regression Analysis Outputs

In the figure 3 depicted above, the values obtained from ANN prediction and regression analysis are compared. As it can be seen that the two predictions confirm to each other. This further validates the newly developed ANN model and hence it can be used for generalisation.

CONCLUSIONS

The current research work discusses the development of an ANN based model used for optimisation and prediction for the aluminium alloy LM6 die casting. The cause and effect analysis is studied in order to find the various parameters having effect on the quality parameter i.e., porosity. The porosity problem is directly linked to the density of the casting which is chosen as output due to the convenience in measuring it. The analysis of variance (ANOVA) is the carried out in order to find out the significant factors out of the five chosen parameters. ANOVA table indicates that the molten metal temperature and the hydraulic pressure are the two most significant parameters affecting the casting density at 90% confidence level. Now these two factors are selected for the ANN modelling. The hundred experimental observations collected from the industry, out of which, 70% is used for training, and 15% for validation and 15% is used for testing purpose. Next, in order to obtain a desired casting density, the corresponding melt temperature and the hydraulic pressure can be predicted from the ANN model. The actual data is compared with the predicted values to find the error. Also the ANN and regression analysis outputs are compared. The two outputs confirm to each other which further confirm the generalisation ability of the ANN model.

Hence it can be concluded that for the incorporation of advanced manufacturing technology in an enterprise, the newly developed ANN based intelligent decision support system is very much useful and suitable. Similar to the present approach, multiple outputs can be considered during ANN modelling to include mechanical properties of the casting for optimization**.**

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